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Single-step attribution of increasing frequencies of very warm regional temperatures to human influence

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Abstract

Seasonal near-surface temperatures have increased in many regions of the World. Previous work has shown that this has led to rapidly increasing frequencies of very warm Northern Hemisphere summer temperatures. Here we show, using a 'single-step' attribution framework, that increases in frequencies of very warm seasonal temperatures, not just in Northern Hemisphere summers but in other regions and seasons, can be directly attributed to human influence. In the June-August and September-November seasons, many of the sub-continental regions of Africa and Asia show robust attributable increase in the frequencies of anomalously warm seasonal temperatures. Copyright © 2011 Royal Meteorological Society, Crown Copyright and Crown in the right of Canada

Keywords: **attribution; climate; regional temperatures**

1. Introduction

The evidence is now very strong that human-induced warming of the climate system is widespread and that increased concentrations of greenhouse gases have very likely led to most of the global warming observed over the last 50 years (Hegerl *et al.*, 2007; Stott *et al.*, 2010). Evidence is also mounting that warming on individual continents can be attributed to human influence, with studies reporting a detectable human influence on warming on all the six inhabited continents of North and South America, Europe, Asia, Australia, Africa (Stott, 2003) and those scattered parts of Antarctica which have *in situ* measurements over the last 50 years (Gillett *et al.*, 2008). When combined with other evidence of a detectable human influence on aspects of the changing climate, e.g. increases in atmospheric moisture content (Santer *et al.*, 2007) and changes in global precipitation patterns (Zhang *et al.*, 2007), it is becoming increasingly evident that the global climate is being altered significantly as a result of human activities.

As a result, some societies could have to adapt to a different climate than they have become accustomed to. Increased frequency of warm spells and heat waves could lead to decreases in water quality and crop yield, and increases in water demand, wild fires, and heat-related mortality (IPCC, 2007). Many impacts are threshold related, with climate-related effects only becoming significant once climate indicators have exceeded particular critical thresholds.

One potential result of on-going global warming is that temperature thresholds that used to be exceeded relatively rarely become exceeded much more frequently. For example in Europe Stott *et al.* (2004) showed that, by 2003 human influence had very likely ($P > 90\%$) at least doubled the probability of European mean summer temperatures exceeding a threshold exceeded in the exceptionally hot summer of that year. This conclusion was based on a model-based calculation of the probabilities of exceeding a particular threshold with and without the effects of human influence on climate. Such model-based probabilities were not directly compared with observational estimates, but depended instead on a calculation of the mean warming attributable to human influence and what this implied for the probabilities of rare events. As the events considered in that paper are still relatively rare, such a direct comparison was not possible, although the authors also pointed out that such events are set to become common by the middle of this century if greenhouse gas emissions continue unabated. The study is an example of a multi-step attribution analysis (Hegerl *et al*., 2009) in which an attribution is made to a change which is not itself detectable (as the events are still so rare) but which is closely linked to a change which is detectable (namely the underlying increase in mean European temperatures).

Given such a projected rapid increase in previously rare events it is interesting to analyse the observations of less rare events, changes in which could currently be detectable, to determine if we can attribute any such changes directly to their causes. Such a direct comparison does not need to make a model-based assumption about how changes in the tails of distributions are related to changes in the mean, as was the case with the multi-step attribution analysis of Stott *et al*. (2004) described above. Jones *et al*. (2008) analysed Northern Hemisphere summer temperatures and showed that there has been a rapid increase in the frequency of unusually warm summers that were once relatively infrequent, being observed only once per decade on average during the 1961–1990 period. They also showed that the HadGEM1 climate model is able to capture many features of this rapid increase and that this current sharp rise is likely to continue.

What Jones *et al*. (2008) did not do was to directly attribute the observed increase in frequency of very warm summer temperatures to anthropogenic and natural causes. However, such a direct or 'single-step' attribution (Hegerl *et al*., 2009) is potentially possible for such events, because they are sufficiently common that the observed evolution of their frequencies can be calculated and directly compared with modelled estimates of their expected evolution due to anthropogenic forcings and natural forcings. Note that the events defined by Jones *et al*. (2008) (and in this paper) are once per decade in each grid box but that frequencies are averaged over all the grid boxes in a sub-continental scale region and therefore there is reasonable sampling of such events. A single-step approach is in many ways preferable to the multi-step approach because it provides a direct link between forcings and response, and therefore does not require an additional assessment of the strength of linkage between multiple steps (Hegerl *et al*., 2009), and because a direct single-step observation-model comparison provides the potential for calibrating model predictions by past observed changes, as has been done for mean temperatures (Stott and Kettleborough, 2002).

Here we carry out a single-step attribution analysis, extending the seasons, regions and models considered by Jones *et al*. (2008) to include all the inhabited land regions of the world and to consider modelling uncertainty by including the two climate models currently available (HadGEM1 and MIROC) that have made multi-member ensembles including anthropogenic and natural forcings separately which continue up to 2008 (rather than stopping in 2000 as most model ensembles do).

Our motivation in this paper is to develop a methodology for carrying out single-step attribution on the frequency of exceeding critical thresholds. Such an approach could be extended to other impact-relevant thresholds such as at daily or sub-daily timescales.

2. Analysis of seasonal frequencies of very warm seasonal temperatures

We consider the 22 sub-continental land regions proposed by Giorgi *et al*. (2001) and compare the observed evolution of temperatures in these regions with those simulated by the HadGEM1 and MIROC climate models. For each model we analyse two ensembles of simulations; in the first ensemble both anthropogenic and natural forcings are included (denoted by ALL) and in the second ensemble only anthropogenic forcings are included (denoted by ANT). There are four simulations in each ensemble of HadGEM1 and ten simulations in each ensemble of MIROC, where each ensemble member differs from the others in having a different initial condition taken from the respective model control simulations (denoted CONTROL) in which external forcings are held constant to provide representations of the effects of internal climate variability. We analyse a 1150-year control simulation of HadGEM1 and a 3600-year control simulation of MIROC. An estimate of the effects of natural forcings alone can be obtained from the difference between the ALL simulations and the ANT simulations. Further details of the HadGEM1 and MIROC models and their forcings are given by Nozawa *et al*. (2005) and Stott *et al*. (2006), respectively.

To calculate the frequencies of exceedance of a particular temperature threshold at any particular time, the same procedure is followed as in Jones *et al*. (2008). All modelled data are masked by the observational data mask, where for observations we use the CRUTEM3v dataset of near-surface temperatures over land (Brohan *et al*., 2006), so that model data are only considered where observational data are available. For the observations and the model simulations, order statistics are used to estimate the 90th percentile of the temperature for each season in each grid box for the 1961–1990 period if at least 25 out of the possible 30 data points are available. We then calculate the fraction of times that threshold is crossed, for each grid box per number of available data points, during a moving 10-year window for all the available data points up to and including 2008. The average fraction of threshold crossings per 10-year interval is calculated for each of the 22 regions for the observations, and for the ALL, ANT and CONTROL simulations of the HadGEM1 and MIROC models, from which we calculate the average estimated probability of a particular

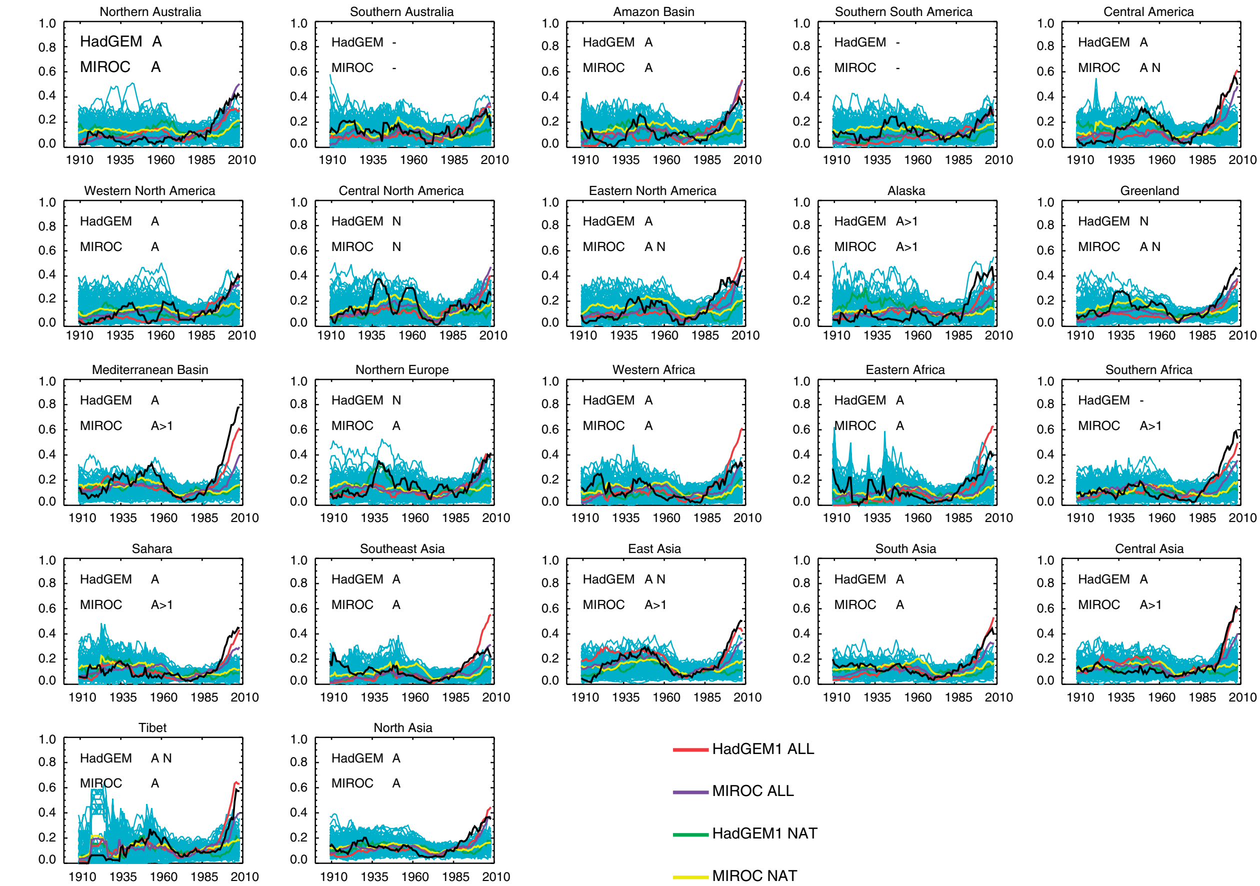

Figure 1. Estimated probabilities of the JJA seasonal mean temperatures being warmer than the 1961–1990 one in ten warmest years for each of the 'Giorgi' regions. Observations are shown in black, and HadGEM1 and MIROC simulations in the colours as indicated in the key. Samples from the control simulation are shown as light blue lines. Where anthropogenic and/or natural forcings are detected they are indicated as A and/or N respectively, and in these cases where the scaling factors from optimal detection are significantly greater than or less than 1 these are shown as >1 or <1, respectively. Where neither signal is detected this is marked as '–'.

grid box in a region exceeding its 'historic' one in ten warm season threshold. By averaging the fractions over all the grid boxes in the region, there is much smaller sampling uncertainty in the overall probability obtained than there would be for each grid box. Previous work has shown that threshold adaptation to the base period that is used for determining the thresholds (in this case 1961–1990) can lead to inhomogeneities in the time series of percentile-based thresholds at the edges of the base period (Zhang *et al*., 2005), but we discuss the impact of this effect below where we use a sensitivity study to show it does not have a major effect on our results. We prefer the threshold calculated from the 1961–1990 base period to thresholds that would avoid this effect, e.g. one calculated over the whole period, as the former allows us to relate frequencies with which thresholds are being exceeded now to their frequencies during a commonly used base period.

The results for the JJA season are shown in Figure 1, where observed changes in estimated probability of exceeding the one in ten warmest season (black lines) are compared with the modelled estimates under both anthropogenic and natural forcings and under just natural forcings for both HadGEM1 and MIROC. Also shown are equivalent changes as estimated from segments taken from the control run of HadGEM1 (blue lines). For many of the regions, observations and model simulations that include anthropogenic forcings show changes that are outside the range of internal variability in recent decades. Also indicated are where an optimal detection analysis (as described in the next section) indicates that the effects of anthropogenic forcings (denoted A) or natural forcings (denoted N) are detected in that region. The largest observed increases in recent decades are seen in Central America, Mediterranean, southern Africa, East Asia, Central Asia and Tibet, in all of which regions the 'historic' one in ten season (estimated from the 1961–1990 period) now appears to have become a 1 in 2 year event and for all of which regions the effects of anthropogenic forcings are detected.

3. Attribution analysis

We carry out optimal detection analyses on changes in the estimated probabilities of exceeding the climatological one in ten seasonal temperatures. We include data from all the regions together in a single global analysis for each season and we also carry out optimal detection analyses for each of the 22 regions separately.

The optimal detection analyses are standard 'total least squares' regression analyses (Allen and Stott, 2003), that seek to explain the observations as a linear combination of the response to anthropogenic forcings, the response to natural forcings and internal variability. Such standard optimal detection analyses are described in detail by Jones *et al*. (2008). Such optimal detection analyses calculate scaling factors by which the modelled response can be scaled up or down while still remaining consistent with the observed response. Where the 5th percentile of a scaling factor is >0, the postulated climate change signal is said to be detected (with a 5% chance of a type 1 error, i.e. the null hypothesis of no influence of the postulated climate change signal is correct).

It is usually necessary to reduce the dimensions of the problem by projecting all data onto the leading eigenvectors calculated from an estimate of the inverse of the covariance matrix of internal variability. Here, we analyse the probability data rather than regional mean temperatures as in Jones *et al*. (2008). We calculate the timeseries of probabilities for each year for a particular season due to anthropogenic forcings from the simulations of HadGEM1 and MIROC that include anthropogenic forcings only, and the timeseries of probabilities due to natural forcings from a linear combination of the simulations including both anthropogenic and natural simulations, and the simulations just including anthropogenic forcings. Equivalent timeseries are calculated from the observational data and for segments taken from the control simulations of the two models.

All data describing probabilities of exceeding the designated thresholds are smoothed using a low-pass filter that removes the frequency components that have a time period <10 years. Hundred years of smoothed data from 1909 to 2008 inclusive are sampled at ten points at the 10-year intervals of 1918, 1928, ..., 2008. The optimal detection analysis is carried out on the natural logarithm of the odds

$$\log(P/(1-P)) \quad (1)$$

where P is the probability. Although probabilities do not combine linearly, the log of the odds does, and therefore this logit function is the natural diagnostic to use in a regression analysis of probabilities (McCullagh and Nelder, 1983).

The responses to anthropogenic and natural forcing are estimated by taking the ensemble mean of the probabilities from the available simulations (four member ensembles for HadGEM1 and ten member ensembles for MIROC) and then the natural logarithm of the odds are calculated for the ensemble means according to Equation (1). For the global analysis, the optimal detection is applied to vectors with 220 components, which are constructed from observations and model simulations, and which are made up of the ten decades of data and the 22 regions. We also carry out optimal detection analyses on each of the 22 regions separately where here the timeseries of ten data points for each region are analysed.

Given our limited sampling within each decade, it is not possible to reliably estimate probabilities <0.05 and >0.95 using this direct calculation and, therefore, we assume that any probabilities <0.05 or >0.95 are actually 0.05 or 0.95, respectively. While this procedure could violate the requirement that the regression model should have normally distributed residuals, we do not find evidence for this when we carry out a 'perfect model' study on the data. When we treat a single member of the MIROC ANT ensemble as though it was an observation and regress it in an optimal detection analysis against the ensemble mean of the remaining nine members (which are then treated as the model estimate of the forced response) and do this for each of the 22 regions, we find that in about 10% of cases, the 5–95% uncertainty ranges of the scaling factors on the anthropogenic signal are not consistent with one, as would be expected if the regression model is behaving correctly.

A necessary requirement for model simulations in any detection analysis is that they are able to adequately represent internal variability. We check this in two ways, by looking at the residuals of regression and checking for any inconsistency between them and the modelled estimates of internal variability (Allen and Tett, 1999), and by comparing spectra of modelled and observed variability (not shown). Both tests indicate that models are generally able to capture the observed variability in the diagnostic considered here for most of the regions considered although there discrepancies in a few regions; in the southern Australian region HadGEM1 appears to overestimate observed variability and in the Amazonia region underestimate it in the JJA season.

Results from the global optimal detection analyses for all four seasons are shown in Figure 2, where results are plotted over a range of truncations (the number of leading eigenvectors onto which the data are projected) from 20 to 40. Anthropogenic forcings are clearly detected in all seasons using both models, whereas there is no such robust detection of natural forcings by both models.

We also carry out optimal detection analyses for each region separately with the results summarised in Table I. In only 3 out of 22 regions – southern Australia, southern South America and central North America – are anthropogenic forcings not detected in JJA using fingerprints derived from either model. There are only two regions in SON, five regions in DJF and three regions in MAM for which the effects of anthropogenic forcings are not detected in either model. Natural forcings are detected in some regions in some seasons but there are far fewer detections that are seen for both the models than for anthropogenic detections: four cases across all seasons for natural detections as against 47 cases for

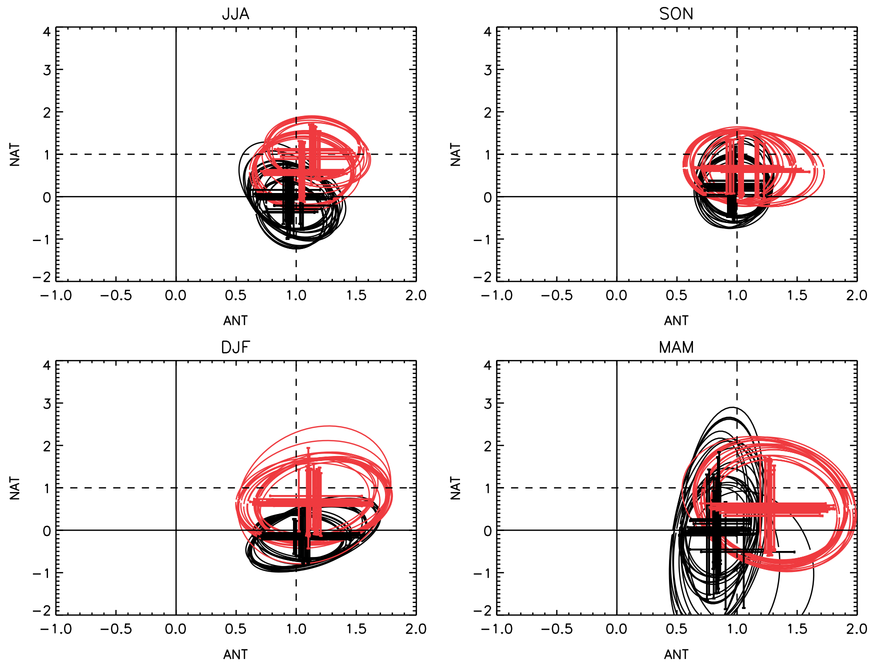

Figure 2. Anthropogenic (ANT) and natural (NAT) scaling factors from the global optimal detection analyses for each season. Results are shown for HadGEM1 (in black) and MIROC (in red) for a range of truncations from 20 to 40. The ellipses show the two-dimensional 95 percentiles and the horizontal and vertical lines show the corresponding one dimensional 5–95% confidence interval for each of the two signals.

Table 1. Detection of anthropogenic and natural forcings by region.

Region	JJA			SON			DJF			MAM		
	ANT	NAT	1 in 2	ANT	NAT	1 in 2	ANT	NAT	1 in 2	ANT	NAT	1 in 2
Alaska	G M			G M			G M	G		G M		
Greenland	M	G M		M			G M	M		G	M	
Western North America	G M			G	G		G M			M		
Central North America		G M			G M		G				M	
Eastern North America	G M	M		M	M		M			G M		
Northern Europe	M	G		G M		Y	M			G M		
Mediterranean	G M		Y	G M			M			M		Y
North Asia	G M			G M			G M			M		
Central Asia	G M		Y	G M		Y		M		M		Y
Tibet	G M	G	Y	G M	M					M		Y
East Asia	G M	G	Y	M		Y	G M			M		Y
Central America	G M	M	Y	G M	M		G	M		M	M	Y
Amazonia	G M										M	
Sahara	G M			G M			G M			G M		
Western Africa	G M			M				G		G M		
Eastern Africa	G M			G M			G M			G M		Y
South Asia	G M			G M		Y	G M		Y	G M		
Southeast Asia	G M			G M			G M			G M	G	
Southern South America				G							M	
Southern Africa	M		Y	G M		Y	G M	G M	Y	G M		
Northern Australia	G M			M			M			M		
Southern Australia				G			M			G		

Where the anthropogenic signal (ANT) or natural signal (NAT) is detected using the HadGEM1 or MIROC model, it is denoted by G or M, respectively, in the relevant column of the table. Where the observations show that a 1 in 10-year event is now a 1 in 2-year event, it is denoted by a Y in the '1 in 2' column.

anthropogenic detections. These regional results, in which there are far more detections of the effects of anthropogenic forcing than of natural forcing, are consistent with the global results which show much more robust detections of the effects of anthropogenic forcings than natural forcings.

Robust detections of anthropogenic forcings are seen in many of the sub-continental regions of Africa and Asia in JJA and SON and the timeseries for SON, shown in Figure 3, like for JJA shows clear increases in the observed frequencies of exceeding the temperature thresholds in many regions. There are a number

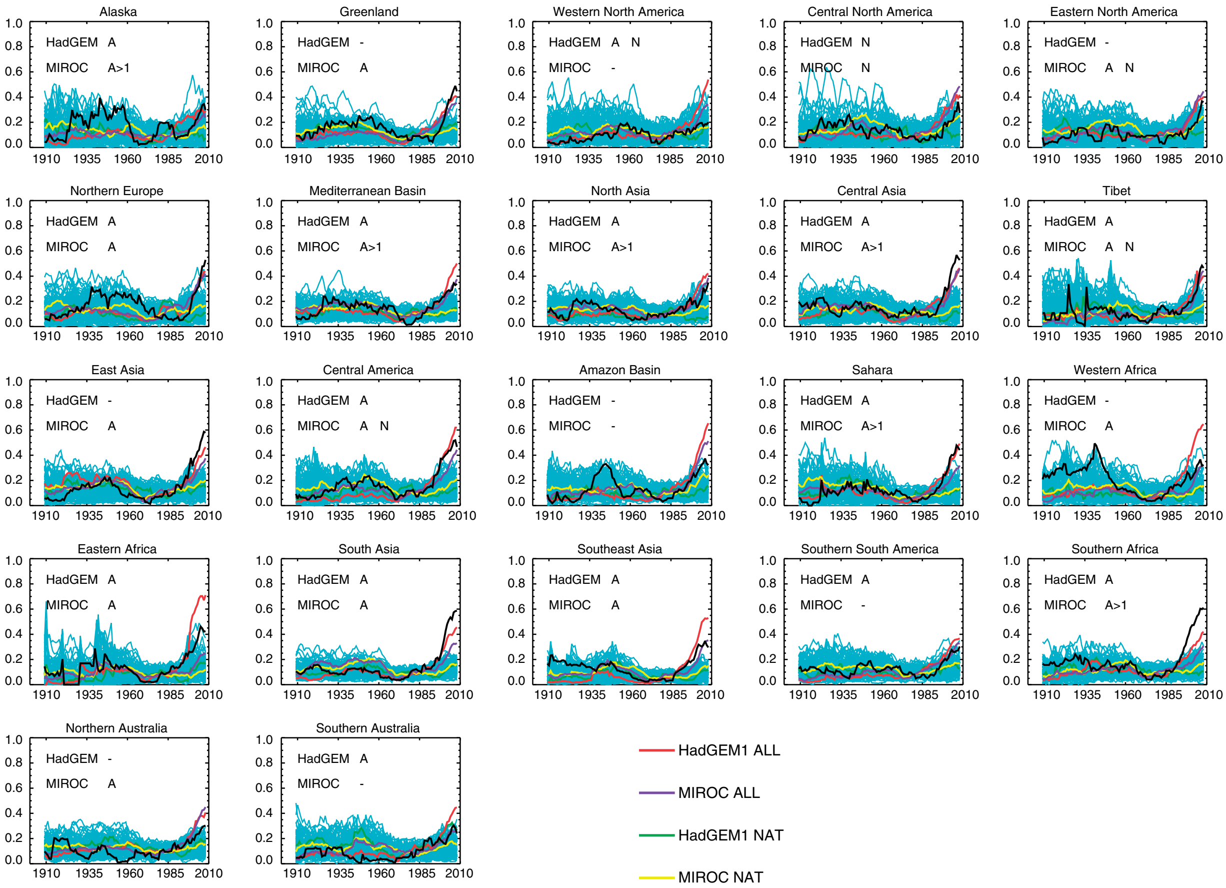

Figure 3. Estimated probabilities of the SON seasonal mean temperatures being warmer than the one in ten warmest years for each of the 'Giorgi' regions. Observations are shown in black, and HadGEM1 and MIROC simulations in the colours as indicated in the key. Samples from the control simulation are shown as light blue lines. Where anthropogenic and/or natural forcings are detected they are indicated as A and/or N respectively, and in these cases where the scaling factors from optimal detection are greater than or less than 1 these are shown as >1 or <1 respectively. Where neither signal is detected this is marked as '–'.

of individual regions over which anthropogenic forcings are detected and for which the scaling factors for MIROC are significantly >1 in JJA and SON (Figures 1 and 3) indicating that the MIROC model underestimates the response in some regions. There are no regions for which either anthropogenic or natural forcings are detected and for which the scaling factors are <1 for either model, i.e. for which the model overestimates the forcing response in JJA.

As discussed above, threshold adaptation to the base period can lead to inhomogeneities (Zhang *et al.*, 2005). However, in our analysis, both the observational and model data are treated identically, as they were in Jones *et al.* (2008), and therefore we would not expect such an effect to favour the detection of one signal over another. Nevertheless, we tested the sensitivity of our results by repeating our analyses using a 1 in 10 years threshold over the entire period analysed rather than just the 1961–1990 period. Our sensitivity studies still find robust detections of anthropogenic forcings globally for each of the four seasons. Regionally, anthropogenic forcings continue to be the dominant factor being detected in far more regions than natural forcings, as shown in Table II. These results support our conclusion that anthropogenic forcings provide the dominant causal factor behind the observed rapid increases in frequencies of unusually warm seasonal temperatures. By using a threshold calculated from the 1961 to 1990 base period, we are able to relate frequencies with which thresholds are being exceeded now to their frequencies during a commonly used base period.

4. Summary and discussion

We have analysed, observed and modelled estimates of the probabilities of exceeding warm temperature thresholds for seasonal temperatures and shown that the observed rapid increases in frequencies seen in many regions can be directly attributed to the effects of human influence. Unlike previous studies, which attributed the observed increase in mean temperatures and then made inferences about the causes of the observed increases in probabilities of temperatures exceeding thresholds, this study makes the link to human influence explicit by carrying out optimal detection analyses directly on the timeseries of frequencies. It also shows that optimal detection analyses of this sort can discriminate between models, identifying instances where a model significantly underestimates the observed increase in frequencies in some regions.

Table II. Detection of anthropogenic and natural forcings by region where the 1 in 10-year thresholds have been calculated over the entire period.

Region	JJA		SON		DJF		MAM	
	ANT	NAT	ANT	NAT	ANT	NAT	ANT	NAT
Alaska	GM				GM		GM	
Greenland	GM		G	M	M	GM	GM	GM
Western North America	GM			GM	GM		M	
Central North America		GM		G	M		M	
Eastern North America	GM		M		M	G	M	
Northern Europe	M	G	G		M		GM	
Mediterranean	GM	G	GM		M			
North Asia	GM		GM	G	GM		M	
Central Asia	GM		GM				M	
Tibet	GM	G	GM		M		M	
East Asia	GM		GM		M		M	
Central America		M	GM		G		GM	
Amazonia	GM		G	M	G			
Sahara	GM		GM				GM	
Western Africa	G		M			G	GM	
Eastern Africa	M		GM	M	GM	G	M	M
South Asia	GM		GM		GM		GM	
Southeast Asia	GM		GM		GM		GM	
Southern South America			G		GM	G	GM	
Southern Africa	GM		M		GM		GM	
Northern Australia	GM		G		M		GM	
Southern Australia		G	GM		M		GM	

The anthropogenic signal (ANT) or natural signal (NAT) is detected using the HadGEM1 or MIROC model, and it is denoted by G or M, respectively, in the relevant column of the table.

This study therefore serves as an example of a 'single-step' attribution as applied to extreme events (Christidis *et al.*, 2005; Hegerl *et al.*, 2009). It is only possible to make such direct model/data comparisons for events that are sufficiently frequent for their changes to be observed directly. However, a possible extension is to derive the statistical properties of extreme events from the observational record and then seek to determine if there have been changes in the statistical distributions over time that can be attributed to anthropogenic or natural causes (Brown *et al.*, 2008; Zwiers *et al.*, (in press)). Single-step attribution could perfectly well consist of multiple models (including dynamical, statistical, etc.) provided they are used to directly attribute the variable of interest whereas multi-step attribution approaches take an indirect approach and rely on an assessment of the strength of the links between separate and disjointed steps.

We have also shown here that the human-induced signal of increased frequencies of moderate extremes has robustly emerged in seasonal temperatures for most of the 22 sub-continental land regions examined. In the JJA season, in six of these regions (Central America, Mediterranean, southern Africa, East Asia, Central Asia and Tibet), we estimate that temperature thresholds that were exceeded for only 10% of years during the 1961–1990 period are now being experienced for more than 50% of years and this is also the case for five regions in the SON season (northern Europe, southern Africa, East Asia, South Asia and Tibet), two regions in DJF (southern Africa and South Asia) and six regions in MAM (Central America, Mediterranean, eastern Africa, East Asia, Central Asia and Tibet). Thus, southern Africa is experiencing warm seasons more than every other year in both summer and winter seasons, whereas frequencies of exceeding such thresholds are not yet being experienced as often as every other year in the winter season in Northern Hemisphere mid or high latitudes. The attributable changes indicate that the observed changes in most regions are broadly consistent with those predicted by the HadGEM1 model and, in a few regions and seasons, could be greater than those predicted by the MIROC model. Our results indicate that human influence rather than natural factors is the major contributor to recent increases in probabilities of warm seasons.

Where a single-step attribution analysis of this sort is possible, it can lend additional confidence to detection of human influence on observed changes and quantification of the relative contributions of anthropogenic and natural factors. In our case, we have shown that significant observed changes have been detected and that these changes are robustly attributable to human influence. Multi-step attribution approaches can still provide valuable information, particularly where events are still very rare, as has been done, e.g. by Stott *et al.* (2004) for the European region and by Christidis *et al.* (2010) for nine sub-continental scale regions provide valuable. When several steps are involved in an attribution analysis, it is important to make an overall assessment of the confidence in the results given the indirect nature of the evidence, as in this case attribution is based on an inference rather than a direct comparison between observations and models (Hegerl *et al.*, 2009).

More models would make the findings described here more robust but currently very few models are available which have the necessary multi-member ensembles of anthropogenic and natural forcings considered separately that also simulate conditions to present. To evaluate evolving risks under a changing climate, it would be advantageous to have a wider range of such model runs available. Such a single-step attribution approach could be extended to a wider range of impact-relevant thresholds.

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